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Research Paper

Applicability of machine learning models for drought prediction using SPI in Kalahandi, Odisha

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ABSTRACT

This study assesses the performance of auto-regressive integrated moving average (ARIMA), artificial neural network (ANN), support vector machine (SVM) and extreme learning machine (ELM), in predicting meteorological drought with Standardized Precipitation Index (SPI-6 and SPI-12) for Kalahandi district, Odisha. Mann-Kendall tests showed no significant trend in SPI value for both shorter and longer scales. Model performance was evaluated using correlation coefficient (CC), root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE), and mean absolute error (MAE) during the training as well as testing phases. For SPI-6, ARIMA performed well during training (NSE = 0.66, RMSE = 0.60) but showed a decline in testing (NSE = 0.25). Machine learning models, including ELM, SVM and ANN exhibited better consistency, with NSE values ranging from 0.45 to 0.47. For SPI-12, ANN delivered the highest accuracy with NSE values of 0.91 and 0.89 and RMSE values of 0.31 and 0.29 in training and testing, respectively. Graphical analysis further demonstrated that ANN and SVM outperformed ARIMA by effectively capturing nonlinear trends and extreme fluctuations. Overall, machine learning models, particularly ANN and SVM, proved to be superior for predicting both long-term (SPI-12) and short-term (SPI-6) precipitation indices, highlighting their effectiveness for accurate drought forecasting.

Keywords: ARIMA, SPI, ELM, SVM, ANN, RMSE, MAE and NSE

Drought is a significant natural hazard, causing extensive harm to human life and ecosystems (Sridhara *et al.,* 2021). The World Meteorological Organization (WMO 2023) highlights the prolonged and unpredictable nature of droughts, making them challenging to manage. Drought is categorized into meteorological, hydrological, agricultural, and socioeconomic droughts (Wilhite and Glantz, 1985; Kanthavel *et al.,* 2023). Various indices have been developed for drought assessment, with the Standardized Precipitation Index (SPI) being one of the most widely used (McKee *et al.,* 1993). SPI is calculated at different timescales, with SPI-6 and SPI-12 being crucial for monitoring seasonal and long-term hydrological droughts, respectively (Sridhara *et al.,* 2021; Lee and Dang, 2018).

The eastern region of India, particularly Odisha, has experienced recurrent extreme weather events such as heat waves and droughts due to its geographical vulnerability (OSDMA, 2016). Odisha, with its agrarian economy, heavily depends on agriculture, making it highly susceptible to droughts. Forecasting droughts is challenging due to their complex nature and varying spatial and temporal scales (Hao *et al.,* 2018). Different models have been employed for drought prediction, including statistical, dynamical, and hybrid models. Statistical models use empirical relationships, dynamical models simulate physical interactions, and hybrid models integrate both approaches for improved accuracy (Strazzo, 2019; Panda, *et al.,* 2023).

Recently, machine learning (ML) techniques have gained prominence in hydro-climatic modelling due to their ability to capture complex nonlinear relationships. ML algorithms such as artificial neural networks (ANN), support vector machines (SVM), and extreme learning machines (ELM) have been applied in temperature forecasting, rainfall-runoff modeling, and drought prediction (Tian *et al.,* 2018; Khan *et al.,* 2024; Pandey *et al.,* 2024).

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These methods offer robust tools for addressing the complexities of drought forecasting, aiding in effective water resource management and mitigation strategies. To address these challenges, the present study aims to develop an ML-based model for drought prediction using the Standardized Precipitation Index (SPI) at two distinct timescales: SPI-6 for shorter durations and SPI-12 for longer durations. This study specifically focuses on the Kalahandi district of Odisha, ensuring a more localized and effective approach to drought forecasting.

MATERIALS AND METHODS

Study area and Data Collection

Kalahandi district is situated in the Tel River sub-basin of Odisha between Latitude 19°54'04" N and Longitude 83°09'56"E. The gridded (0.25^0 X 0.25^0) rainfall data from 1970 to 2021 over Kalahandi district of Odisha were collected from India Meteorological Department (IMD) and were used for drought analysis using standardized precipitation index (SPI).

Standardized precipitation index (SPI)

The SPI analyzed the meteorological drought across various timescales, including shorter scales SPI-6 and longer scales SPI-12, using monthly precipitation records. Initially, the monthly rainfall data is fitted to a suitable probability density function (PDF), with the Gamma PDF often identified as the most suitable for SPI evaluation in many studies (McKee *et al.,* 1993). Probabilities are then calculated from the monthly precipitation records, which are subsequently standardized into a standard normal distribution with a mean of zero and a unit standard deviation. In this research gamma distribution is used for calculation of SPI at various time scales. The categorization of drought class is based on criteria given in Table 1

Mann-Kendall trend test

The Mann-Kendall test was used to detect monotonic trends in the time series data. As a nonparametric method, it does not require assumptions about the underlying data distribution and is robust against outliers due to its rank-based nature. The test provides the Kendall Tau (τ), a rank correlation coefficient that measures the monotony of the trend's slope, ranging from 1 to -1. A positive "**τ**" indicates a growing tendency, while a negative "**τ**" indicates a declining tendency. This approach ensures reliable detection of significant trends over time while minimizing the influence of extreme values or non-normal data distributions.

Table 1: Categorization of different drought class based on SPI

Class type	SPI Value
Extremely dry	−2.00 and less
Severely dry	−1.50 to −1.99
Moderately dry	−1.00 to −1.49
Mild dry	0 to -0.99
Normal	0.99 to 0
Moderately wet	1.00 to 1.49
Very wet	1.50 to 1.99
Extremely wet	2.00 and above

Prediction of drought using ARIMA and ML techniques

In this research, three machine learning methods, ELM, SVM, and ANN, and autoregressive integrated moving average (ARIMA) models were employed for predicting drought. ARIMA model is widely used statistical technique for time series forecasting due to its effectiveness in capturing temporal dependencies (Patil *et al.,* 2020). While the ML approach integrates advanced models such as extreme learning machine (ELM), support vector machine (SVM), and artificial neural networks (ANN), which have demonstrated strong capabilities in handling nonlinear relationships in hydrological modeling (Suliman*,* 2024; Deo and Sahin, 2015). Following SPI computation, both model types undergo training and testing to evaluate their predictive performance. The accuracy of these models is assessed using statistical metrics, including Root Mean Square Error (RMSE), Correlation Coefficient (CC) and Mean Absolute Error (MAE), ensuring a comprehensive performance comparison.

Model development and evaluation

For model development, input features were determined based on partial correlation function (PACF) and auto correlation function (ACF) analyses. All model simulations were conducted using ELM, SVM, and ANN algorithms in the "MATLAB 2020" environment. The dataset, covering 51 years (1970–2021), was divided into two parts: the training phase (1970–2010) and the testing phase (2011–2021). After training the proposed networks for each machine learning technique, a weight matrix was attained and applied over independent inputs of the test set. Finally, the results were equated with the actual values obtained from the SPI.

RESULTS AND DISCUSSION

Mann-Kendal test of SPI-6 and SPI-12

The results of the Mann-Kendall test, displayed in the Fig. 1, indicate that Kendall's Tau (τ) value of 0.02, which reflects a very small positive trend. However, the p-value of 0.56 suggests that this trend is not statistically significant**.** This means the observed slight increase could be attributed to random variability rather than a meaningful pattern. In summary, while the visual trend line suggests a slight increase in SPI-6 values, the statistical analysis does not provide strong evidence to support this trend. The fluctuations in the SPI-6 values highlight the variability in precipitation conditions

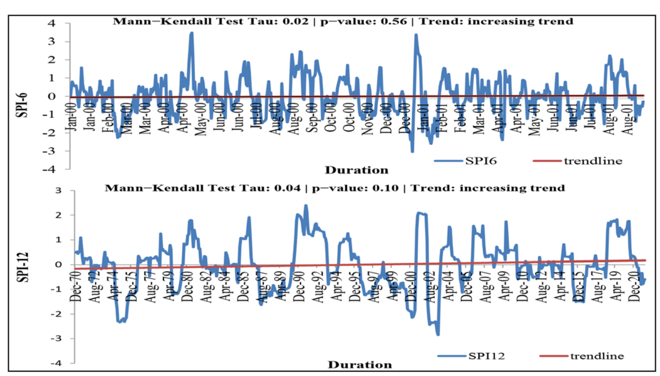

Fig. 1: Temporal variation with Mann-Kendal test of SPI-6 and SPI-12

Table 2: Frequency of different drought month at different class

Time scale	Extremely dry	Severely dry	Moderately dry	Mild
SPI-1	4	15	41	247
SPI-3	7	30	54	247
SPI-6	15	33	56	230
SPI-9	8	34	46	217
SPI-12	5	36	48	214

over the given duration. The Kendall's Tau (τ) value of 0.04 indicates a minor positive trend in the SPI-12 values, while the p-value of 0.10 suggests that this trend is not statistically significant at the 95% confidence level but approaches moderate significance. This implies that although an upward trend in long-term precipitation is visually apparent, the statistical evidence is not strong enough to confirm it conclusively.

Frequency of drought events at Kalahandi district

The frequency of drought months across different SPI timescales reveals variations in drought severity. From the Table 2 it was observed that the SPI-1, which represents short-term drought conditions, there were 4 extremely dry months, 15 severely dry months, 41 moderately dry months, and 247 mild drought months. As the timescale increases, the frequency of severe and extreme droughts generally rises. SPI-3 recorded 7 extremely dry months, 30 severely dry months, 54 moderately dry months, and 247 mild drought months, indicating a more persistent impact compared to SPI-1. SPI-6, which captures seasonal drought trends, showed the highest count of extremely dry months (15), along with 33 severely dry, 56 moderately dry, and 230 mild drought months. In the case of SPI-9, representing longer-term drought patterns, there were 8 extremely dry, 34 severely dry, 46 moderately dry, and 217 mild drought months. Similarly, SPI-12, which reflects long-term hydrological droughts, recorded 5 extremely dry, 36 severely dry, 48 moderately dry, and 214 mild drought months. The trend suggested that shorter timescales (SPI-1 and SPI-3) exhibit more frequent mild droughts, whereas longer timescales (SPI-6, SPI-9, and SPI-12) depict a gradual increase in severe drought occurrences, highlighting the persistence and intensity of prolonged drought conditions.

Forecasting of SPI-6 and SPI-12 by ML and ARIMA model

The SPI was calculated at shorter and longer scale time frames. As shown in Fig. 2 and Fig. 3, PACF was applied to determine the optimum lags of the SPI index (Deo and Sahin, 2015). The lag values that provide this 95% confidence bound were selected as the inputs. This study investigates the input-output relationships for predicting the SPI at shorter and longer time scales (SPI-6, and SPI-12). Based on the ACF and PACF plots shown in Fig. 2 and Fig. 3, was observed that for the smaller scale (SPI-6), lags t-1, t-6, and t-7 are used as inputs, while for the longer scale (SPI-12), lags t-1 and t-13 are selected as inputs.

Evaluation of ML models

It was evident from Table 3 that the models' performance was assessed for both SPI-6 and SPI-12 based on the NSE and RMSE values. For SPI-6, ARIMA showed the best training phase

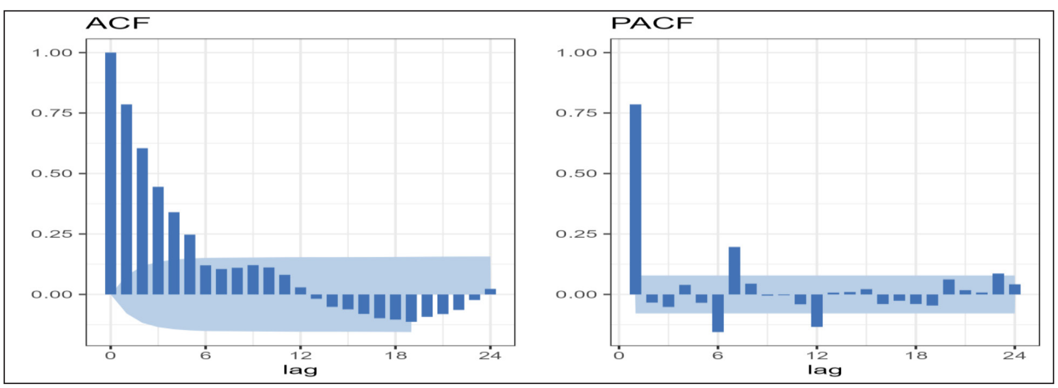

Fig. 2: Autocorrelation function and partial autocorrelation function for SPI-6 (with 5% significance limits) for Kalahandi district

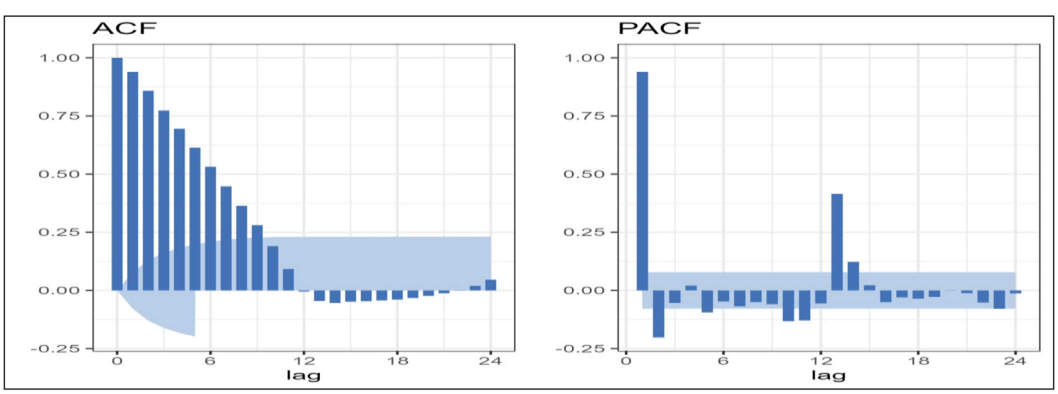

Fig. 3: Autocorrelation function and partial autocorrelation function for SPI-12 (with 5% significance limits) for Kalahandi district

Table 3: Evaluation metrics of the model outputs for various timelines during the training and testing periods for Kalahandi

Model Name	Input-output feature	Training periods				Testing periods			
		CC	MAE	RMSE	NSE	CC	MAE	RMSE	NSE
SPI-6									
ELM	SPI_{t-1}, SPI_{t-6} and SPI_{t-7}	0.80	0.45	0.61	0.64	0.69	0.44	0.63	0.47
ANN		0.80	0.45	0.62	0.64	0.69	0.44	0.63	0.46
SVM		0.80	0.45	0.63	0.63	0.7	0.44	0.63	0.45
ARIMA		0.81	0.44	0.60	0.66	0.71	0.44	0.62	0.25
SPI-12									
ELM	SPI_{t-1} and SPI_{t-13}	0.94	0.21	0.34	0.89	0.94	0.19	0.30	0.88
ANN		0.95	0.19	0.31	0.91	0.94	0.18	0.29	0.89
SVM		0.94	0.2	0.35	0.89	0.94	0.18	0.30	0.88
ARIMA		0.94	0.21	0.34	0.89	0.19	0.94	0.34	0.86

performance with the highest NSE value of 0.66 and the lowest RMSE of 0.60, indicating better accuracy in capturing short-term dependencies. However, during testing, ARIMA's NSE dropped significantly to 0.25, showing a decline in predictive reliability, while other models such as ELM, ANN, and SVM demonstrated more consistent testing performance with NSE values of 0.45–0.47 and RMSE around 0.63. Among these machine learning models, SVM and ANN stand out for their ability to adapt to complex and dynamic variations, while ELM also shows competitive performance with improved responsiveness to rapid changes. Overall, machine learning models outperform ARIMA, demonstrating their effectiveness in accurately predicting SPI-6.

For SPI-12 ANN achieved the best performance in both training and testing phases from Table 3 recorded the highest NSE value of 0.91 and the lowest RMSE of 0.31 during training, and maintained strong results in testing with an NSE of 0.89 and RMSE of 0.29. ELM and SVM followed closely, with similar testing phase results (NSE = 0.88 and RMSE = 0.30). ARIMA also performed well for SPI-12, with an NSE of 0.89 and RMSE of 0.34 during training, though its testing performance slightly lagged behind other models with an NSE of 0.86 and RMSE of 0.34. It was concluded that Machine learning models (ANN, SVM, and ELM) outperform ARIMA for both SPI-6 and SPI-12 forecasting, with ANN and SVM showing the highest accuracy in capturing trends, peaks, and nonlinear fluctuations. Patil *et al*., (2020) compared the ARIMA and ANN models for SPI-6 (shorter scale) and long-term forecasting, reporting RMSE values of 0.69 and 0.53 for SPI-6, and 0.59 and 0.35 for the longer scale, respectively, validating the superior performance of the ANN model. Similarly, Lalika *et al.,* (2024) evaluated the SVM and ELM model, finding NSE values 0.82 and 0.59 respectively for prediction of SPI-6.

CONCLUSION

This study highlights the comparative performance of different forecasting models ARIMA, ANN, ELM, and SVM in predicting the SPI values for Kalahandi District, Odisha, specifically for short-term (SPI-6) and long-term (SPI-12) periods. The results of the Mann-Kendall test indicated no statistically significant trends in SPI values, suggesting that the observed slight increases in precipitation over time were likely due to random variability. In terms of model performance, ARIMA demonstrated strong results during the training phase for SPI-6 but showed significant limitations during testing, especially in capturing nonlinear trends. In contrast, machine learning models, particularly ANN and SVM, exhibited superior consistency and predictive power. ANN emerged as the most effective model for SPI-12, delivering high accuracy both during training and testing phases. For SPI-6, while the machine learning models outperformed ARIMA, however, ANN, ELM, and SVM displayed comparable performance in capturing the complexity of short-term precipitation variability. These results have significant implications for improving drought forecasting and water resource management, suggesting that integrating advanced machine learning models could lead to more robust and dynamic forecasting tools for regions prone to drought, such as Kalahandi District.

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Authors' contributions: **Amit Prasad:** Collection of data, analysis of data, writing the manuscript, data maintenance, software, and original draft. **R. K. Singh**: advisory committee chair, conceptualization, methodology, peer review, and editing. **K. V. R. Rao**: provided technical input on data analysis, and edited the manuscript. **C.K. Saxena**: reviewed and edited the manuscript.

organizations they belong to.

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